Flexible Design and Operation of a Smart Charging Microgrid

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Abstract

The reliability theory of repairable systems is vastly different from that of non-repairable systems. The authors have recently proposed a 'decision-based' framework to design and maintain repairable systems for optimal performance and reliability using a set of metrics such as minimum failure free period, number of failures in planning horizon (lifecycle), and cost. The optimal solution includes the initial design, the system maintenance throughout the planning horizon, and the protocol to operate the system. In this work, we extend this idea by incorporating flexibility and demonstrate our approach using a smart charging electric microgrid architecture. The flexibility is realized by allowing the architecture to change with time. Our approach "learns" the working characteristics of the microgrid. We use actual load and supply data over a short time to quantify the load and supply random processes and also establish the correlation between them. The quantified processes are then used to generate load and supply realizations over the long planning horizon. We show how this can reduce the computational effort when simulating microgrids for the entire planning horizon without impeding on their design under various operating scenarios considering uncertainty.

1. Introduction

Microgrids are systems of interconnected sources and loads. If a microgrid is not connected to a major city utility, it is considered islanded where it is likely part of an emergency operation with a major utility not available [1]. While the best use of reliable microgrids is encountered in remote areas, including war zones, it is also at these locations that one must consider the implications of reliability. A reliable microgrid supports the loads with minimum service interruptions, with little fuel and component resupply and at a reasonable cost. Consequently, a microgrid system optimization problem involves multiple conflicting objectives. One objective is to maximize a measure of reliability which is defined as the ability of the online sources to power the online loads without turning them off unexpectedly. Other objectives include cost and the number of failures encountered within the planning horizon (lifecycle). Because the microgrid is a repairable system (defined below), the classical notion of reliability is not directly applicable. For this reason, we use the Minimum Failure Free Period (MFFP) as a surrogate for reliability [1-3].

For repairable systems, the amount and frequency of repair affects how one perceives their reliability or more generally, their "performance." The classical notion of reliability, defined as the probability that the system has not failed before a given time t, can be misleading because a repairable system may have failed before time t and have been repaired [4]. The classical reliability definition can also impede decision making involving maintenance, availability and service cost of such systems. Although an appropriate maintenance strategy can make a system available most of the time, it cannot compensate for too many service interruptions and a potentially high service cost. The tradeoffs between performance, service interruptions and cost are hard to capture. Pandey and Mourelatos [2] have recently shown that we can systematically approach the design and maintenance of repairable systems using a Minimal Set Of Metrics (MSOM) to capture most of the information about the working conditions and repairability of such systems. In this paper, we extend the methodology in [2] and apply it to a smart charging electric microgrid.

If a microgrid model is available, we can perform mathematical optimization over the discussed attributes. The optimization problem is generally set up as a non-linear mixed integer problem because of the non-linear objective function and the combination of discrete and continuous decision variables [5]. The power-load balance for the microgrid is managed by turning on and off sources and loads based on how much a load or source is above or below a required point (set points). There are other conditions as well such as the number of sources and loads, and inventory. The optimization problem can be solved using system simulations over a short time duration (e.g., hours) which requires extrapolation of results over the long planning horizon (e.g., one year), or by using a coarse time scale over the long time horizon. The former leads to a major disconnect between mathematical optimization and its actual implementation where the decision maker worries about long-term metrics such as Mean time Between Failures (MTBF) and cost, while computational issues guarantee that only short periods (or coarse time scales) can be simulated and hence optimized. As a result, one faces three issues:

1. **Incorrect extrapolations:** We must rely on extrapolations of results to consider the entire operating time which

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14. ABSTRACT
The reliability theory of repairable systems is vastly different from that of non-repairable systems. The authors have recently proposed a ?decision-based? framework to design and maintain repairable systems for optimal performance and reliability using a set of metrics such as minimum failure free period, number of failures in planning horizon (lifecycle), and cost. The optimal solution includes the initial design, the system maintenance throughout the planning horizon, and the protocol to operate the system. In this work, we extend this idea by incorporating flexibility and demonstrate our approach using a smart charging electric microgrid architecture. The flexibility is realized by allowing the architecture to change with time. Our approach ?learns? the working characteristics of the microgrid. We use actual load and supply data over a short time to quantify the load and supply random processes and also establish the correlation between them. The quantified processes are then used to generate load and supply realizations over the long planning horizon. We show how this can reduce the computational effort when simulating microgrids for the entire planning horizon without impeding on their design under various operating scenarios considering uncertainty.

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generally includes multiple years. Unless done properly, what is learned in a short simulation time may not be applicable to the entire planning horizon.

2. **Coarse time scales:** The simulation time intervals are too long. Many transient effects are not captured properly because they happen within seconds. A simulation using large time steps may miss these effects. The flip-side is that fine time scale simulations are computationally prohibitive.

3. **Uncertainty:** The effect of uncertainty cannot be fully captured. For example, we may encounter a chance failure and assume that the microgrid is unreliable or alternatively by luck, we may not see any failure in a short period even if the microgrid is unreliable.

The approach in this paper is different from classical approaches. It proposes "learning" from a short time operation and extrapolating to a longer period such as the planning horizon. The running protocol of a microgrid involves two elements – the total load the microgrid must service and the total supply it uses to service it. The "learning" we propose, refers to the random process of the overall load and the random process of the supply in response to the load. This ensures that the relative levels of load and supply are captured and the correlation between their evolutions in time is also captured. Once the characteristics of load and supply are learned (i.e., their random processes are quantified), we can extrapolate them into the future to calculate long-term reliability metrics. This extrapolation is theoretically sound because it preserves the statistical characteristics of the load and supply processes as opposed to extrapolating the results of a short-time simulation. Short simulations are prone to missing extreme events and therefore, the relative frequency of events is likely to be miscalculated. Modeling of the entire process does away with this limitation.

As we show in Section 2, a repairable system must be designed over multiple metrics that capture different facets of the system performance. We will show how to calculate the metrics of the system using a characterized (quantified) random process approach. Consequently, this work provides a framework to perform complicated analyses of microgrid operating scenarios. Remote systems have become more electrified over time and their power needs and generation capabilities have increased. Their optimal operation is therefore, critical. Available optimization methods using long-duration simulations are not however, practical because of the required computational effort. There are also many new concepts such as "gridable" vehicles that need to be analyzed. When vehicle systems link into other systems such as a microgrid in order to share power sources and loads, a vehicle-to-grid (V2G) system is formed [6]. Analysis of such microgrids is very complicated and a method that can extrapolate what is learned in a short time period can be very useful.

The paper is organized as follows. Section 2 describes the proposed methodology and discusses a metric-based design approach of repairable systems using a minimal set of metrics and stochastic process modeling using time series. Section 3 demonstrates the proposed methodology using a smart charging microgrid example. Finally, Section 4 summarizes, concludes and discusses future research directions.

2. Methodology

2.1 Metric-based design of repairable systems

Classical reliability theory uses metrics such as the Mean Time Between Failures (MTBF) and availability to characterize the performance of a repairable system [4]. These metrics are calculated using times between failures and system repair frequency and durations. However, each of them captures only one statistic of the time to failure. The MTBF for example, captures the mean, while the availability is simply the ratio of system up-time to the total duration a system is in operation. A system that has a skewed distribution of the time between failures will not have its performance well represented by the MTBF or availability. To account for these limitations, we have proposed using a Minimal Set of Metrics (MSOM) to describe the performance of repairable systems [2]. The MSOM should be defined so that the metrics, individually or collectively, cover most aspects of the system performance. The reader is referred to our previous work for a detailed description of the topic [2]. For the microgrid example in this paper, we use the metrics of cost (C), minimum failure free period with 80% probability ($T_{0.8}$), and number of failures (N_f) within the planning horizon. A Pareto front is generated over the metrics, which are then traded off by the decision maker to find the optimal combination that best satisfies his/her preferences.

2.2 Proposed approach and computational issues

Microgrids contain many interconnected loads and sources. At each time, the running protocol decides, based on load requirements, how many sources to keep on, what capacity to run them at, and how much excess capacity to have in order to account for stochastic variations in load. Clearly, if we characterize the load random process and know therefore, its behavior through time, we can account for sudden load changes by suitably increasing or decreasing the supply. However, we cannot always do this perfectly because of inherent uncertainty in load and because of partial system failures. As mentioned earlier, the failures can be due to inadequate capacity to service the load or to actual subsystem failures. Cost considerations may also preclude a microgrid that never fails. Thus, failures are expected. For a dynamic system such as a microgrid, it is very difficult to predict its long term performance without actually simulating the grid for a long duration. Considering that most electrical transients happen in milliseconds, we needs to run simulations with a very short time interval for months at a time in order to fully account for them. This is obviously computationally impractical.

We propose to "learn" the characteristics of the load profile $L(t)$ and the resulting supply profile $S(t)$, as enacted by an intelligent power management protocol. It is necessary to not only characterize the random processes $L(t)$ and $S(t)$ but also the correlation between them. This is because a supply that is not well correlated with load will either lead to many failures, wasted power, or both. A short period of a few days can be used for the "learning" process. Based on the quantified stochastic behavior, we can then extrapolate the two random processes for a long time (e.g., several months or even years) and record the number of failures where the supply is less than the load (Figure 1) and the times failures occurred. This

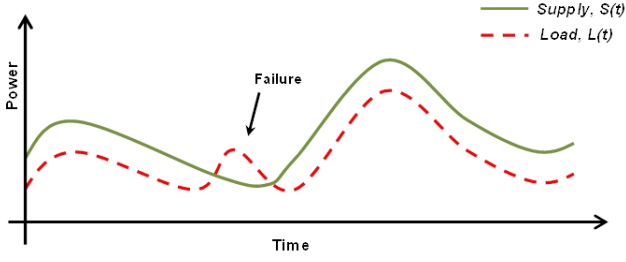information can be used to quantify the system performance metrics.

Figure 1. Realizations of the supply and load random processes

2.3 Overview of time series modeling of load and supply random processes

We use a time series model to characterize the load and supply random processes. Time series models have been extensively used to characterize a random process [7]. They combine Auto-Regressive (AR) models, Integrated (I) models, and a Moving Average (MA) model. The Integrated (I) model is used if the process is non-stationary. All models use a feedback mechanism based on either past observations, past standard errors (MA), or a combination of the two, to determine future observations. AR models are the most commonly used. They provide a weighted average of past observations in addition to a white noise error term, to capture the correlation at instances t_1 and t_2 where $\tau = t_2 - t_1$ is small.

Consider a random process $X(t)$. A sample function $x(t)$ is discretized in the time interval [0, T] using a uniform time step Δt so that $x_i = x(t_i)$ and $t_i = i \cdot \Delta t$. For a p order AR model, denoted as AR(p), the discretized sample function is represented as

$$x_i - \mu = \phi_1(x_{i-1} - \mu) + \phi_2(x_{i-2} - \mu) + \ldots$$
$$+ \phi_p(x_{i-p} - \mu) + \varepsilon_i \qquad \text{(1a)}$$

where μ is the temporal mean of the process, $\varepsilon_i \equiv N(0, \sigma_e^2)$ is Gaussian white noise and $\phi_1, \phi_2, \ldots., \phi_p$, are feedback parameters to be estimated. The above equation can also be used to create a derivative process as

$$y_i = \mu_i + L(x_i) \qquad \text{(1b)}$$

where μ_i is the mean of the process $Y(t)$ at time i, x_i is a zero mean process modeled using the AR model of Equation (1a), and L is a function of x_i. To preserve stationarity of x_i after an existing trend is removed, L must be linear and μ_i constant.

After the feedback parameters are estimated in Equation (1a), a residual series $E(t) = X(t) - \hat{X}(t)$ is formed as the difference between the actual $X(t)$ and the estimated $\hat{X}(t)$ processes and statistical tests are performed to make sure that the random variables E_t and $E_{t+\tau}$ are uncorrelated for every τ. Details are provided in [7].

3. Smart Charging Microgrid Example

3.1 Essentials of a microgrid and design details

A smart microgrid is used in remote locations to provide reliable power to critical installations. Microgrids incorporate intelligent power management to enable a robust and reliable operation and offer substantial fuel and maintenance economies over their service life. Most microgrids consist of an AC module and a DC module. The former connects and disconnects different sources and loads and handles the AC power. The function of the latter is to manage the DC sources (batteries and solar arrays), invert them to get AC power and supply it to the AC module. Commonly used sources in a microgrid are utility mains if available, generators, solar arrays, windmills and rechargeable vehicles. The sources are given priority numbers which determine the reverse order in which they will be taken offline, if necessary. A low number indicates that the source is critical and will be taken offline after the other sources have already been taken offline. The load side of the microgrid is modeled explicitly. The sources and loads are shed and added depending on the system's excess capacity. In general, loads include building loads, battery charging loads, and other miscellaneous loads. Similarly to sources, each load has a priority number.

The microgrid implements control by sensing power usage at various loads and routing power to and from several system components to bring the system to the desired state of operation. This entails switching contactors on or off. When initiated, the grid starts at the system equilibrium and remains in this state unless/until the excess system capacity moves outside specified set-points. Excess capacity is defined as the available power in excess of the current load. The microgrid is assumed failed if it cannot meet the load requirements, i.e., the instantaneous supply $S(t)$ is less than the instantaneous load $L(t)$. There are various scenarios where this can happen such as the total capacity is not enough to meet an unexpected spike in load, one or more sources or contactors have failed, a software error in implementing the control has occurred, or any combination of the above. A failure requires to either repair a failed component or wait for the microgrid to recover if the supply capacity is reached (soft failure).

In our previous work [2] in order to design the microgrid, we solved the multiobjective optimization problem of Equation (2) using the Non-dominated Sorting Genetic Algorithm – II (NSGA-II) [8]. The objectives of total cost C (initial cost $C_{initial}$ plus repair cost C_{repair}) and number of failures N_f within the planning horizon P are minimized and the objective of minimum failure free period with 80% probability $T_{0.8}$ is maximized. The decision variables are the set-points

$s_{ls}, s_{so}, s_{lo}, s_{ss}$ where the loads and sources are taken offline/online and the number of sources $n_{gen}, n_{solar}, n_{contacts}$ (generators, solar arrays and contactors) we start with.

$$\underset{\mathbf{x}}{Min}\{-T_{0.8}, N_f, C\}$$

where $\mathbf{x} = \{s_{ls}, s_{so}, s_{lo}, s_{ss}, n_{gen}, n_{solar}, n_{contacts}\}^T$

$$T_{0.8} = F_{T_{working}}^{-1}(0.2)$$

$$C = C_{initial} + C_{repair}$$

subject to:

$$P = 8760$$

$$n_{gen}, n_{solar}, n_{contacts}, n_{batt} \in N$$

$$s_{ls}, s_{so}, s_{lo}, s_{ss} \in [0, 100]. \quad (2)$$

The formulation of Equation (2) indicates that the simulation is run for $P = 8760$ hours (1 year) for each value of the design variable vector. This introduces a substantial computational effort because for each of the 8760 hours, we must simulate the workings of the microgrid by sensing the load, turning off/on sources and loads accordingly and by repairing/replacing components as needed. To get around this issue, we propose to simulate the microgrid for only a short period of time (much shorter than the one year planning horizon) and use the simulated results to characterize the supply and load processes. This is possible only if the stochastic part of the processes after subtracting the trend is stationary. In other words, we propose to use short time data to "learn" the statistical characteristics of the process for the entire planning horizon. Subsequently, realizations of the characterized processes are used to calculate the attributes in Equation (2) without carrying out simulations.

To demonstrate our approach, we assume that the microgrid load is a derivative process as in Equation (1b). The random process part is represented by the zero-mean fourth-order AR model of Equation (3) where time t is measured in hours. For a real simulation, the time series model is determined from actual load realizations observed over a short period of time.

$$L(t_i) = 150 + 100\sin\left(\frac{2\pi t}{24}\right) +$$

$$50\left(\begin{array}{l}0.0345\ \varepsilon_{i-1} + 0.1552\ \varepsilon_{i-2} + 0.2069\ \varepsilon_{i-3} + 0.2586\ \varepsilon_{i-4} \\ + 0.3448\ \varepsilon_i\end{array}\right)$$

$$(3)$$

The load of Equation (3) has a trend with a stable element of 150 kW and a sinusoidal element with period of a day and an amplitude of 100 kW. The latter simulates diurnal changes. The stochastic part has four feedback parameters and a white noise term represented by the standard normal random variable ε_i. The standard deviation of the white noise at each time step is 50×0.3448 = 17.24 kW. The standard deviation of the process $L(t)$ is equal to

$$50 \times (0.0345 + 0.1552 + 0.2069 + 0.2586 + 0.3448) = 50\text{kW}.$$

The supply is modeled by the same fourth-order AR model of Equation (3) with two changes. First, the white noise is correlated with the load white noise and second, there is an excess capacity built-in to ensure that the supply is generally greater than the load. Two strategies are considered for implementing the excess capacity; Strategy 1: Multiply the deterministic part of the load by a factor of $(1 + \phi)$, and Strategy 2: Add a fixed additional power δ to the modeled load. Equations (4) and (5) with ω_i being a standard normal random variable, express the two strategies.

$$S(t_i) = (1 + \phi)\left(150 + 100\sin\left(\frac{2\pi t}{24}\right)\right) +$$

$$50(0.0345\omega_{i-1} + 0.1552\omega_{i-2} + 0.2069\omega_{i-3} + 0.2586\omega_{i-4} + 0.3448\omega_i)$$

$$(4)$$

$$S(t_i) = \delta + 150 + 100\sin\left(\frac{2\pi t}{24}\right) +$$

$$50(0.0345\omega_{i-1} + 0.1552\omega_{i-2} + 0.2069\omega_{i-3} + 0.2586\omega_{i-4} + 0.3448\omega_i)$$

$$(5)$$

The correlation between ε_i and ω_i is denoted by $\rho_{\varepsilon\omega}$ and is always less than one. The higher its value, the better the supply control algorithm of the microgrid can determine the instantaneous value of the required instantaneous supply. A value of 1 implies that the supply is perfectly correlated with the load and thus, a supply to meet the load can be created with theoretically no excess capacity. If sufficient capacity exists, the microgrid will never fail unless some of its components fail. In this paper, we vary the value of $\rho_{\varepsilon\omega}$ to investigate its effect on the microgrid performance metrics. Figure 2 shows one realization of the load and supply processes according to Equations (3) and (4) for $\rho_{\varepsilon\omega} = 0.9$ and $\phi = 0.25$. We note that the supply is generally higher than the load, except for some infrequent chance failures because of the load stochasticity.
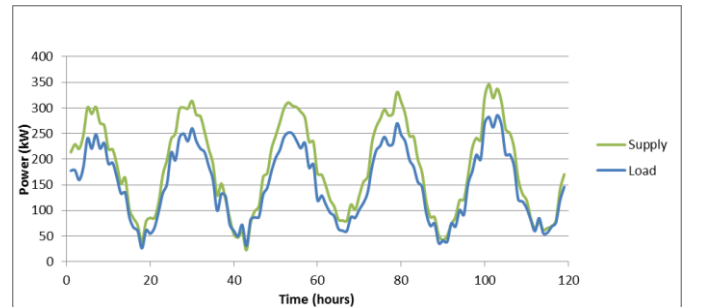

Figure 2. Realizations of load and supply processes for Strategy 1.

3.2 Attributes

The microgrid is optimized over the three long term metrics of cost, MFFP and number of failures. In our opinion, the cost of operation C is best measured by the cost of excess capacity the grid generates over time. This is expected to be less than the cost of setting up and running the microgrid. The reasoning behind this choice is that it is imperative to meet the requisite loads and as such, the cost to do so cannot be considered a good performance metric for the grid. A grid can be expensive if it must meet higher load requirements, and cannot be called worse than a grid that is cheaper only because the load requirements are low. The best grid therefore, is the one that best allocates the excess power to minimize failures.

In this example, the cost of generating power is assumed equal to 10 cents per kWh. The number of failures N_f is simply the number of distinct times the grid fails during the planning horizon of one year. Recall that the proposed method can be used to analyze a grid for many years with a very small additional computational effort. The third metric of MFFP, $T_{0.8}$, is calculated using the running durations of the grid between failures and is simply the 20th percentile of the running durations.

3.3 Sensitivity analyses

This section presents sensitivity analyses for different model parameters and optimal solutions for Strategy 2 (see paragraph above Equation 4). We show that Strategy 2 is a better way to build-in excess capacity. We first compare the two Strategies to build excess capacity according to Equations (4) and (5). Realizations of the microgrid load and supply random processes are generated for 8760 hours. For comparison purposes, we calculated the values of ϕ and δ in Equations (4) and (5) that give the same number of failures during the planning horizon. Fixing for example, the number of failures at 65, we observe that Strategy 1 generates 328,695.3 kWh of excess energy over the course of the year if $\phi = 0.25$. This amounts to $32,869.53 in money spent for insurance against chance failures. On the other hand, Strategy 2 with an excess power of 20 kW generates only 176,917.5 kWh of extra energy, which amounts to $17,691.75. This simple example illustrates that building extra supply capacity as a percentage of load is wasteful because when the load is high, there is less likelihood of it increasing substantially anymore while the opposite is true when the load is low. Therefore, we should build extra capacity in terms of fixed power in kW and not as a percentage of load. For this reason, we use Strategy 2 for further analysis.

Next, we perform a sensitivity analysis of the number of failures and the cost as a function of the correlation coefficient between the load and supply noise terms (Equations 4 and 5). Figure 3 shows the expected decrease in the number of failures. The failures reduce to zero when the supply is perfectly correlated with the load. While this seems intuitive, there are two main points. First, good modeling of the load and responding with a supply that meets that load quickly are essential for a reliable microgrid. Second, the computational cost is low because when the supply is equal to the stochastic load plus a fixed load δ, we can directly calculate the surplus generation (and hence cost) over a year by simply multiplying the number of operating hours by δ.
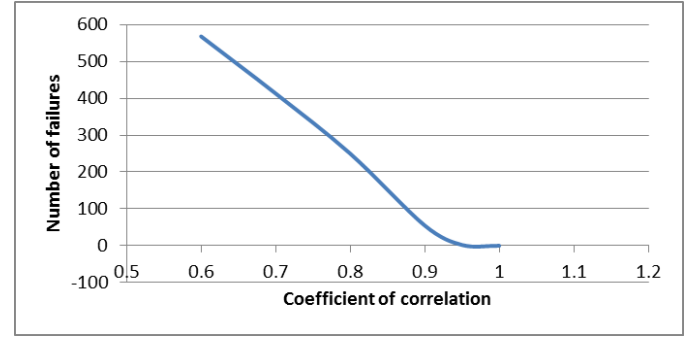

Figure 3. Effect of increased correlation between load and sources on number of failures.

We now concentrate on the optimal solution using Strategy 2. We will determine the optimal extra power (excess capacity) δ in Equation (5). Since the problem involves multiple attributes we expect to get multiple non-dominated solutions. Figure 4 shows the Pareto front over the two attributes of cost and number of failures. The decision maker can use it to choose the most desirable combination of attributes based on his/her preferences. Recall that there are three attributes. For simplicity, the attribute of MFFP is not shown. If the decision maker selects the design with an approximate cost of $21,602 and 8 failures (see Figure 4), the optimal solution provides an excess supply of $\delta = 25$ kW and a corresponding MFFP value of 97.4 hours if $\rho_{\varepsilon\omega}$ is equal to 0.9. As we have mentioned, it is essential to properly quantify the load and source processes and the correlation between them.
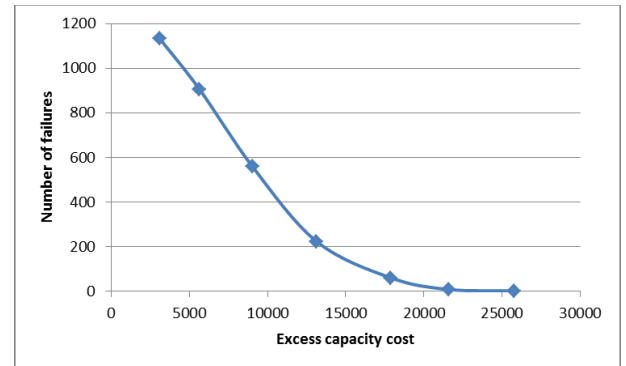

Figure 4. Tradeoff between cost from excess capacity and number of failures for Strategy 2.

4. Summary, Conclusions and Future Work

Microgrids, a collection of power sources for a specialized use, must be reliable at a reasonable cost. We must simulate the microgrid operation for a long period of time in order to properly quantify the load and supply random processes and obtain the optimal microgrid design by trading off a number of performance metrics. The simulations are computationally expensive and as a result many shortcuts are taken in the literature. For example, either coarse time scales are used thereby ignoring transients, or the simulation is run for a short period of time and meaningful performance metrics over the

microgrid long planning horizon are estimated using extrapolation.

This paper addressed this important issue using a different approach. We proposed using actual load and supply data over a short time to quantify the load and supply random processes and also establish the correlation between the two processes. The quantified processes are then used to generate load and supply realizations over the long planning horizon and calculate performance metrics of interest such as cost, number of failures and MFFP. Because actual simulations are performed over a short time, the computational cost is minimal. We showed that this is a feasible strategy which can be used to optimize microgrids over various metrics and also perform sensitivity analysis on various model assumptions.

There are two conclusions from the present study. First, we should model the load process as accurately as possible, thereby increasing the chance that the supply will be higher than the load at any time during the planning horizon. Second, an optimal supply can be obtained by adding a fixed amount of power to the value of the stochastic load at any time instead of a percentage of the load.

In future work, we will quantify the load and supply random processes using actual simulations of the microgrid. We foresee a method that uses actual simulation of a microgrid over a short time to obtain optimal microgrid designs over a long planning horizon that can be realized with minimal computational effort.

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